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Unsupervised Pattern Classifier for Abnormality-Scaling of Vibration Features for Helicopter Gearbox Fault Diagnosis

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A new unsupervised pattern classifier is introduced for on-line detection of abnormality in features of vibration that are used for fault diagnosis of helicopter gearboxes. This classifier compares vibration features with their respective normal values and assigns them a value in [0, 1] to reflect their degree of abnormality. Therefore, the salient feature of this classifier is that it does not require feature values associated with faulty cases to identify abnormality. In order to cope with noise and changes in the operating conditions, an adaptation algorithm is incorporated that continually updates the normal values of the features. The proposed classifier is tested using experimental vibration features obtained from an OH-58A main rotor gearbox. The overall performance of this classifier is then evaluated by integrating the abnormality-scaled features for detection of faults. The fault detection results indicate that the performance of this classifier is comparable to the leading unsupervised neural networks: Kohonen's Feature Mapping and Adaptive Resonance Theory (ART2). This is significant considering that the independence of this classifier from fault-related features makes it uniquely suited to abnormality-scaling of vibration features for fault diagnosis.

Keywords: Condition monitoring; Diagnostics; Gearbox; Vibration

1. Introduction

Present helicopter gearboxes are significant contributors to both maintenance costs and flight safety incidents. Power trains comprise almost 30% of maintenance costs and 22% of mechanically related malfunctions that often result in loss of life and aircraft [1]. Therefore, improved fault diagnosis of helicopter gearboxes is important for saving lives and reducing maintenance costs. Fault diagnostic systems which can detect failures reliably and rapidly will eliminate the need for routine disassembly of the gearbox and allow scheduling of maintenance before a catastrophic failure occurs.

Fault diagnosis of helicopter gearboxes (like most rotating machinery) is based upon vibration monitoring. Since detecting gearbox faults based on the raw vibration signal is usually difficult, features of vibration such as the Root Mean Square (RMS), Kurtosis, Skewness, etc. are extracted to identify various types of faults. A considerable effort has been directed towards development of signal processing schemes for identification of individual features that would be affected by specific faults in the gearbox [2–8]. However, such a one-to-one approach to fault diagnosis has not been feasible because of the complexity of the gearbox, diversity and severity of component faults, presence of noise in the measured vibration, and variations in the operating conditions.

A more comprehensive approach to fault diagnosis which compensates for some of the difficulties of the one-to-one approach is the multiple-feature approach. The common means of feature integration in this approach is pattern classification through connectionist networks [9–12], where the decision regions representing various faults are defined by the connection weights of these networks. Connection weights are usually formed through supervised training using a sample set of feature–fault data. Fault diagnosis is then performed by classifying the vibration features into the decision regions that represent various faults. An important property of connectionist networks is their ability to form decision regions with non-linear boundaries which enables them to represent non-linear relations between features and faults. Their disadvantage, however, is their reliance on supervised learning, which requires feature–fault data for training. Since training data are usually not available and

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through expensive experiments, supervised diagnostic networks are limited in applicability.

In order to avoid the prior training required by supervised diagnostic networks, the authors have proposed an unsupervised network that incorporates the knowledge of gearbox structure for diagnosis [13]. The inputs to this Structure-Based Connectionist Network (SBCN) are abnormality-scaled vibration features (see Fig. 1). Therefore, a method needs to be developed to identify and scale the abnormality of vibration features. This paper introduces the unsupervised pattern classifier designed for this purpose. This classifier performs abnormality-scaling of each feature by relying solely on its value from the normal operation of the gearbox. As such, it is referred to as Single Category-Based Classifier (SCBC) to signify its independence from feature values associated with faulty conditions. In order to perform abnormality-scaling, the SCBC compares features with weights representing their normal-mode values, and if they are 'sufficiently different', assigns values between 0 and 1 to characterize their degree of deviation from the weight values. While the SCBC has a unique design that is specific to the problem at hand, many of its features are similar to those in Kohonen's Feature Mapping (KFM) [14] and Adaptive Resonance Theory (ART2) [15]. For example, like KFM, it uses Euclidean distance as a measure of similarity between the features and their normal-mode values, or similar to ART2, it does not require the abnormal values of features for classification.

Another important feature of SCBC, which is similar to ART2, is its on-line adaptation capability whereby the weight values are updated so as to cope with changes due to noise and variations in process conditions. In general, without sample features associated with faulty cases it is very difficult to distinguish abnormalities due to noise from those caused by faults. Accordingly, there is always the risk that the weights may be inadvertently replaced with those associated with a faulty case. In order to improve reliability of adaptation in SCBC, the weights are updated with regard to the status of other features. Adaptation in SCBC is performed in two stages: *primary adaptation* and *secondary adaptation* [15].

In primary adaptation, a weight is updated to be closer to the value of the feature classified as normal. In secondary adaptation, the weights associated with the rest of the features are updated to be closer to

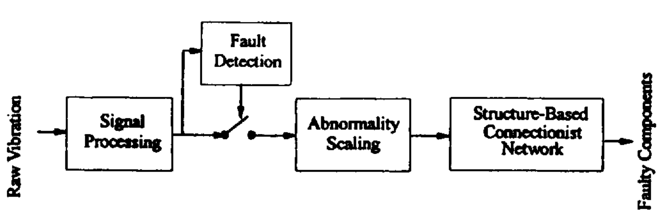

Fig. 1. Overview of fault detection and diagnosis in the proposed structure-based diagnostic system.

their current values if this feature was classified as normal, and to be away from their current values if the feature was classified as abnormal. Primary adaptation is designed to cope with drift in feature values due to process variations. Secondary adaptation on the other hand, is incorporated so as to achieve homogeneity in classification. The rationale for secondary adaptation is that if the majority of features are classified as normal, then the gearbox is healthy and the minority features are classified as abnormal due to noise. So, the normal values of these minority features need to be updated to improve homogeneity in classification. Both primary adaptation and secondary adaptation are recursively performed using a set of recent feature vectors so as to avoid dominance of individual feature vectors in adaptation and better capture the drift in vibration features.

The performance of the SCBC is tested in abnormality-scaling of experimental vibration features obtained from an OH-58A helicopter main rotor gearbox. For this, vibration data reflecting the effect of various faults were processed through a microcomputer customized for vibration signal processing to obtain features of vibration. These vibration features were then abnormality-scaled by SCBC as a prerequisite for fault diagnosis. In this paper, in order to test the performance of SCBC, the abnormality-scaled features were evaluated for fault detection. For this purpose, these features were weighted and integrated. The detection results obtained compare favourably to those obtained from KFM and ART2 methods, which is reassuring given that SCBC is considerably less constrained in its applicability due to its independence from fault-related features.

2. Single Category-Based Classifier (SCBC)

The design of the Single Category-Based Classifier (SCBC) is best described in the context of the problem constraints. This classifier is required to classify individual vibration features according to their level of abnormality, which is not readily possible by either of the two unsupervised pattern classifiers: Kohonen's Feature Mapping (KFM) [14] and Adaptive Resonance Theory (ART2) [15]. KFM performs classification by measuring the distance of the feature vector from the centre of various decision regions formed during an off-line training phase. As such, KFM is limited in applicability due to its need for feature values associated with the fault category. The other method of unsupervised pattern classification, Adaptive Resonance Theory (ART2), classifies a feature vector as normal unless it is 'sufficiently different' [15] from its nominal value. 'Sufficient difference' in ART2 is measured by a 'vigilance' ρ as:

$$\rho_j = \sum_{i=1}^{n} f(s_i, w_{ij}) \tag{1}$$

where the function f determines the match between the feature s_i and the weight value w_{ij} associated with the jth decision region. The advantage of ART2 over KFM is that it does not require any sample features associated with the fault category. Its drawback, however, is that it categorizes feature values that are multiples of the weight w_{ij} within the same category. A limitation that is common to both KFM and ART2 is that they are not designed for scalar classification, which is a requirement in abnormality-scaling of individual features for fault diagnosis.

2.1 Abnormality-Scaling

The schematic of the Single Category-Based Classifier (SCBC) is shown in Fig. 2. The inputs to SCBC are features $s_i(t)$, $i = 1,\ldots,n$, and its outputs are abnormality-scaled features $f_i(t)$ with values between 0 and 1. The value of 0 indicates normality, and the other extreme of 1 denotes complete abnormality. The weights of the SCBC w_i represent the normal values of the features, which are initially set equal to the first set of feature values supplied to the SCBC.

Classification in SCBC is performed by first measuring the distance of each feature $s_i(t)$ from its weight value w_i, and then normalizing it into the range [0,1] using a 'matching factor' ϕ_i, defined as (see Fig. 3):

$$\phi_i(t) = 1 - \exp\frac{-(s_i(t) - w_i)^2}{w_i^2} \tag{2}$$

A ϕ_i value of 0 indicates that the feature value matches the weight value precisely, and a value of 1 indicates that it deviates considerably. Note that the exponential function used here is not unique and that other functions which can map the distance into the range [0,1] can also be used for the matching factor. Since during normal operation of the gearbox, noise in the features causes drifts in the normal values, a threshold θ is considered to account for such drifts within the noise level. The threshold θ is used to hard-limit $\phi_i(t)$ in SCBC as:

$$\phi_i(t) = \begin{cases} o & \text{if } \phi_i(t) < \theta \\ \phi_i(t) & \text{otherwise} \end{cases} \tag{3}$$

In the above relationship, the threshold θ is obtained as:

$$\theta = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \exp\frac{-[max(s_i) - \mu_i]^2}{\mu_i^2}\right) \tag{4}$$

where $max(s_i)$ denotes the maximum value of the ith feature in a set of κ samples of this feature recorded during normal operation, and μ_i represents its mean, estimated as

$$\mu_i = \frac{1}{\kappa}\sum_{t=1}^{\kappa} s_i(t) \tag{5}$$

The matching factor defined by Eq. 2 squashes any positive value in $[0, \infty]$ into the range [0, 1]. As such, only very large deviations in feature values will be scaled to the value of 1. Since such large deviations in feature values are uncommon for gearboxes, the value of matching factor is further scaled to yield abnormality-scaled feature values $f_i(t)$ as (see Fig. 3):

$$f_i(t) = f_{min} + \exp[\alpha^* \phi_i(t)] \tag{6}$$

where f_{min} represents the minimum abnormality value assigned to any feature that violates the threshold θ, and α controls the slope of the exponential curve. Since $f_i(t)$ is defined to have a value between 0 and 1, it is set to 1 when $f_i(t)$ in Eq. (6) exceeds the value of 1.

2.2 Adaptation

After each round of classification of the vibration features, the weight values in the SCBC are updated so as to cope with noise and small variations in the operating conditions. Adaptation is carried out in two stages. In the first stage, called primary adaptation, a network weight is adapted if the feature associated with it is classified as normal. In the second stage, referred to as secondary adaptation [15], the rest of the weights are adapted to achieve homogeneity in the abnormality-scaled values, thus increasing the likelihood of all of them being classified as normal or abnormal. Achieving this homogeneity, however, needs to be carried out with respect to specific feature groups, because individual gearbox faults do not necessarily cause abnormality in all the features. For example, a gear fault will be reflected only by the features related to the gear and is not expected to cause abnormality in bearing features. In order to preserve the functionality of individual groups of features (i.e., general features, gear features, bearing

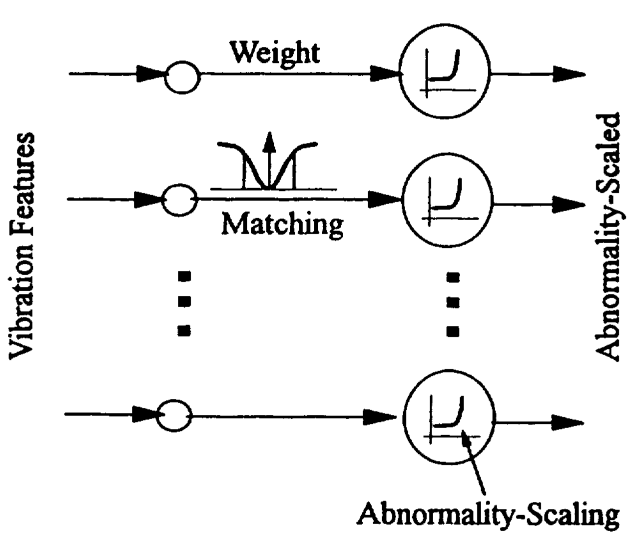

Fig. 2. Schematic of the SCBC.

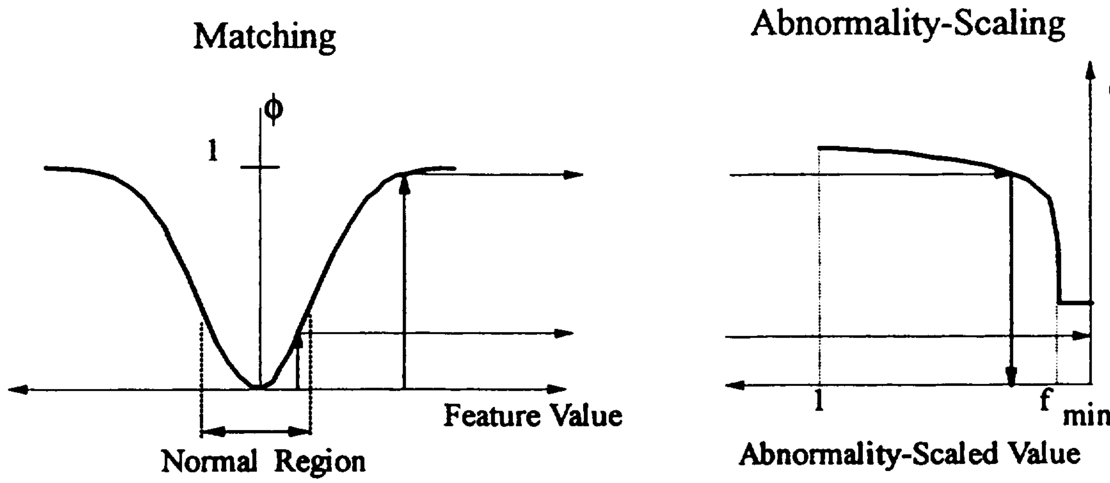

Fig. 3. Matching and abnormality-scaling in SCBC.

features), secondary adaptation is performed exclusively for each feature group.

Adaptation in SCBC is performed as follows: let w_I represent the weight which is presently being updated and w_i the remaining weights in the group. In primary adaptation, the weight value w_I is modified according to the relationship

$$w_I = w_I + \delta w_I \tag{7}$$

where

$$\delta w_I = \begin{cases} \eta[s_I(t) - w_I] \text{if} f_I(t) = 0 \\ 0 \qquad\qquad \text{otherwise} \end{cases} \tag{8}$$

The parameter η in Eq. (8) denotes the learning rate.

For secondary adaptation, if the majority of features are classified as normal, then the weight values associated with the features classified as abnormal will be adjusted such that the likelihood of all the features being classified as normal is increased for the same feature values. Secondary adaptation is performed as

$$w_i = w_i + \delta w_i \text{ for all } i \neq I \tag{9}$$

where

$$\delta w_i = \begin{cases} \eta\Lambda[s_i(t) - w_i] \quad \text{if} f_I(t) = 0 \\ -\eta\Lambda[s_i(t) - w_i] \text{ otherwise} \end{cases} \tag{10}$$

In secondary adaptation, the amount by which the weight values are adjusted is controlled by a neighbourhood function Λ [14] which is assigned a value between 0 and 1. A value of 0 is used for inputs with no noise, and a value at the other extreme of 1 is used for unreliable features with large amounts of noise. Usually in practice the value of Λ is set less than 0.5. For each round of primary adaptation (Eqs (7) and (8)), I is varied to include all the features in the group. If the jth group of features contains m_j features, then primary adaptation is applied by varying I from 1 to m_j to cover all the weight values w_I in the jth feature group. For each I, the remaining weight values w_i in the group (i = 1 to m_j and $i \neq$ I) are adapted using secondary adaptation according to Eqs (9) and (10).

The adaptation algorithm presented in Eqs (7)–(10) is biased towards the most recent feature vector if only this vector were used for adaptation. Ideally, adaptation should be performed using all the feature vectors that pertain to the current operating conditions. But as the number of available feature vectors for each operating condition progressively increases, adaptation based on all the features becomes computationally demanding. As a compromise, in SCBC only the β most recent feature vectors are utilized for each adaptation sweep such that adaptation is performed iteratively over the β most recent feature vectors. The learning rate η is progressively reduced for each adaptation iteration.

3. Experimental

The effectivness of SCBC is evaluated using experimental vibration data from an OH-58A helicopter main rotor gearbox (see Fig. 4). In this section, the experimental setup and signal processing of the vibration are described.

3.1 Setup

Vibration data were collected at the NASA Lewis Research Center as part of a joint NASA/Navy/Army Advanced Lubricants Program [16]. Various component failures in the OH-58A main rotor transmission were produced during accelerated fatigue tests. The vibration signals were recorded from eight piezoelectric accelerometers (frequency range of up to 10 kHz) using an FM tape recorder. The signals were recorded once every hour, for about one to two minutes per recording (using a bandwidth of 20 kHz). Two magnetic chip detectors were also used to detect

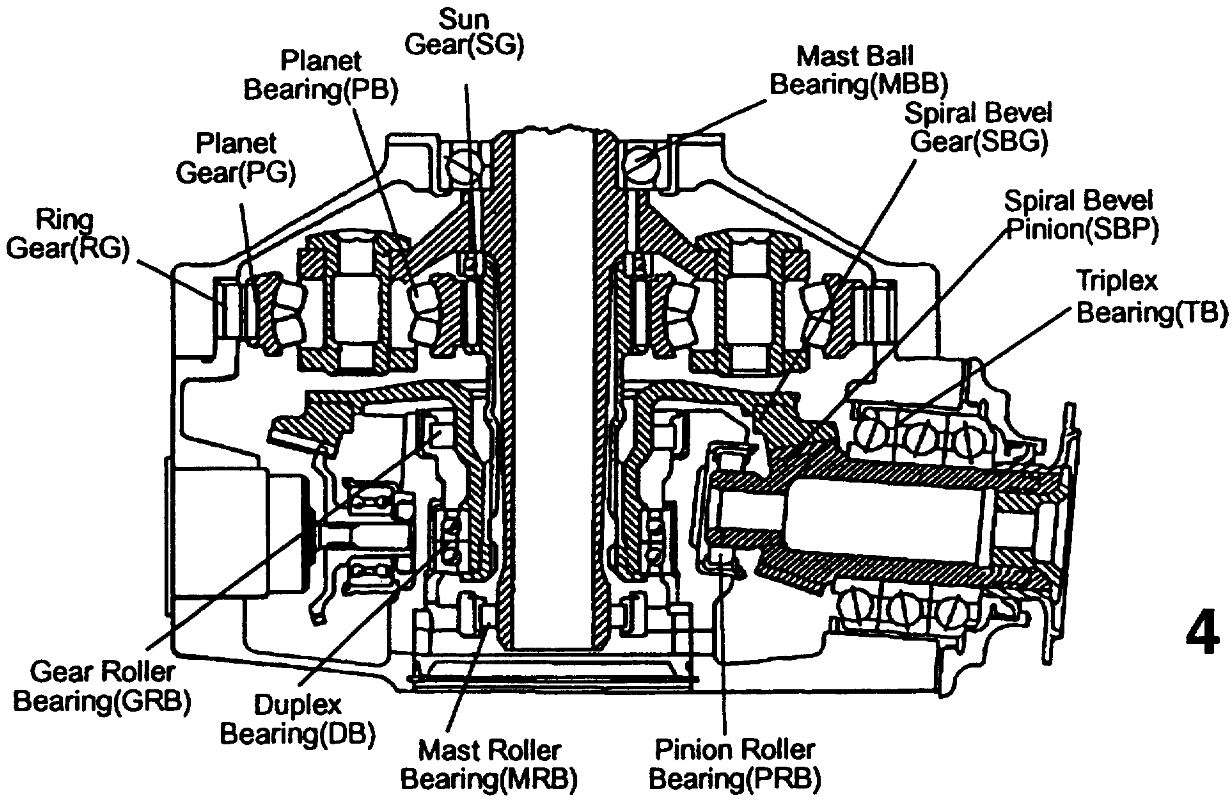

Fig. 4. Layout of the various components in the OH-58A gearbox.

the debris caused by component failures. The location and orientation of the accelerometers are shown in Fig. 5.

In these experiments the gearbox was run under a constant load and was disassembled and inspected periodically, or when one of the chip detectors indicated a failure. A total of five tests were performed, where each test was run between nine and fifteen days for approximately four to eight hours a day. Among the eleven failures which occurred during these tests (see Table 1) there were three cases of planet bearing pitting fatigue, three cases of sun gear pitting fatigue, two cases of top housing cover cracking, and one case each of spiral bevel pinion pitting fatigue, mast bearing micropitting, and planet gear pitting fatigue. With respect to fault detection during these tests, the chip detectors were reliable in detecting failures in which a significant amount of debris was generated, such as the planet bearing failures and one sun gear failure. The remaining failures were detected during routine disassembly and inspection.

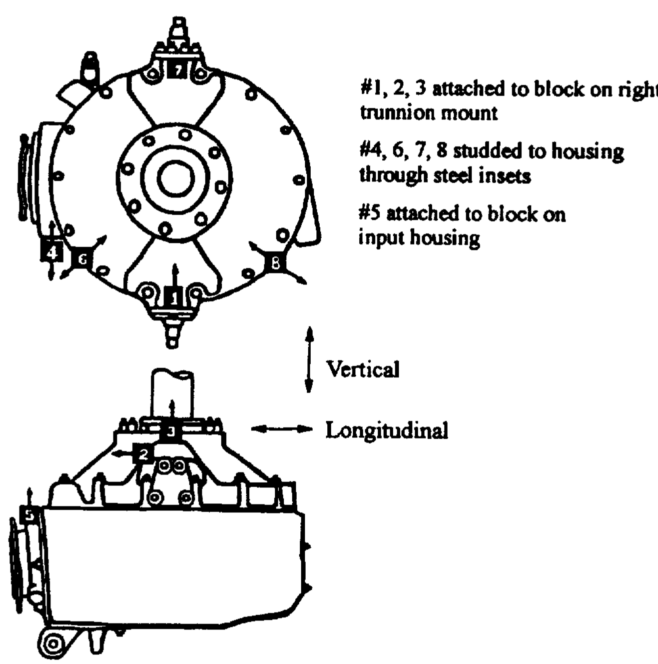

Fig. 5. Location of the accelerometers on the test stand.

3.2 Signal Processing

In order to study the effect of faults on the measured vibration signals, the vibration features were digitized and processed by a commercially available signal analyser with three processing modules [17]:

Table 1. List of faults that occurred during the OH-58A experiments

Test	Number of days	Failures
1	9	Sun gear tooth pit Spiral bevel pinion scoring/heavy wear
2	9	None
3	13	Planet bearing #2 inner race spall Top cover housing crack Planet bearing #2 inner race spall Micropitting on mast bearing
4	15	Planet bearing #3 inner race spall Sun gear tooth pit
5	11	Sun gear teeth spalls Planet gear tooth spall Top housing cover crack

(1) Statistical Analysis (STAT), (2) Baseband Power Spectrum Analysis (BBPS), and (3) Bearing Analysis (BRGA) (see Fig. 6). Overall, nineteen vibration features were extracted for each accelerometer, which were indicators of either general faults (e.g., wear and out of balance), or generalized gear or bearing faults. A brief description of these vibration features in presented in Table 2. For a more detailed description the reader is referred to [18].

4. Detection Results

The effectiveness of SCBC was investigated in abnormality scaling of vibration features obtained from the OH-58A helicopter gearbox. The nineteen features obtained from the three signal processing modules

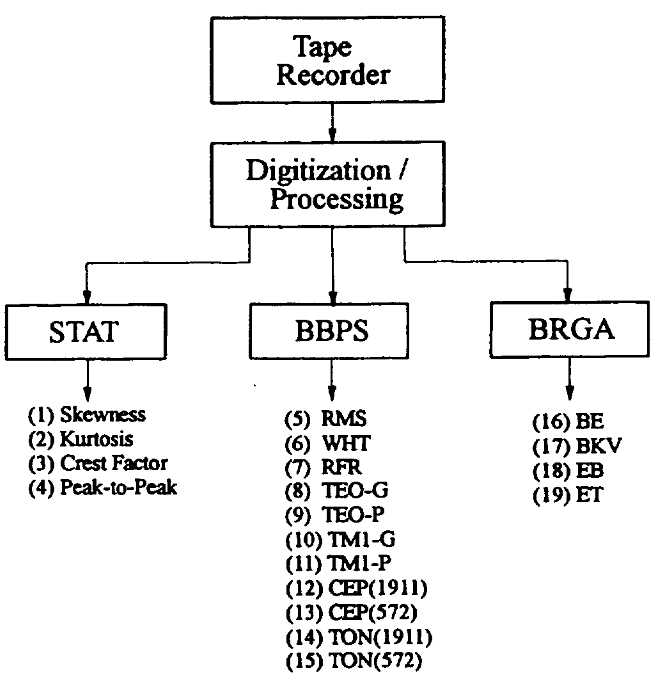

Fig. 6. The vibration features obtained from the signal analyser.

Table 2. List of vibration features and their description

Feature	Description
(1) Skewness	Measures the asymmetry of probability density function (p.d.f.) of the vibration amplitude, which is assumed to be near Gaussian when the machinery is healthy
(2) Kurtosis	Represents the fourth moment of a p.d.f. It is responsive to localized defects affecting the tails of the p.d.f. of the vibration amplitude
(3) Crest Factor	Represents the 'peakness' (flat or peaked) of the p.d.f.
(4) Peak-to-Peak	Represents the difference between maximum and minimum values of the vibration signal
(5) RMS	Represents the overall energy level of vibrations
(6) WHT	Represents the RMS level of the signal minus its strong tones
(7) RFR	Denotes the position of the 'centre of gravity' of the spectrum
(8) TEO–G (9) TEO–P (10) TM1–G (11) TM1–P	Quantifies the RMS (–G) and mean value (–P) of the spectral ratio between the current spectrum and a baseline spectrum. The baseline spectrum could be from the beginning of the test (TEO) or from the previous record (TM1)
(12) CEP(1911) (13) CEP(572)	From metacepstral analysis, used to detect the energy levels of periodic aspects of the vibration signal at the tooth meshing frequency of the spiral bevel pinion and gear (1911 Hz), and the fundamental frequency of the planet bearings (572 Hz)
(14) TON(1911) (15) TON(572)	Represents the energy level associated with a particular tone (1911 Hz or 572 Hz) within a spectrum. It is a good indicator of faults such as unbalance and misalignment
(16) BE	Represents the overall energy level of the envelope which is sensitive to most bearing faults
(17) BKV	Denotes the kurtosis value of the envelope, expected to reflect impulsive vibration signals due to localized bearing faults
(18) EB	Represents the base energy of the envelope after all tones have been removed. It is expected to reflect heavy bearing damage
(19) ET	Represents the total energy minus the base energy of the envelope, expected to reflect localized bearing faults

were used as inputs to SCBC. The initial weight values of SCBC were assigned the values of the first set of features obtained at the beginning of each of the five tests. The subsequent feature vectors obtained from each accelerometer were then abnormality-scaled with the value of the threshold θ set to 0.5 and the value of α to 20. After each feature vector was classified, the weights of SCBC were adapted using primary and secondary adaptation. The vibration features were divided into three separate groups consisting of 8, 5, and 6 features representing general faults, gear faults, and bearing faults, respectively, and secondary adaptation was performed exclusively for each group. The total number of adaptation sweeps through each batch was set equal to 100, where the learning rate was decreased as the inverse of the number of training sweeps. The neighbourhood function was set to 0.05.

In order to evaluate the results, the abnormality-scaled features were integrated for fault detection. For this, the individual abnormality-scaled features were mapped into a scalar through a 'weighting network'. The weights of this network, hereafter referred to as the voting weights, were defined based on the significance of individual features to overall fault detection. For example, if all the n features were assumed to be equally significant, then each voting weight would be set as $1/n$. In this application, the same grouping used for adaptation was used for assigning voting weights. In cases where the m_j features in each of the k groups were equally significant, and each group was to be assigned equal overall weight, the voting weights were defined as $1/(k^*m_j)$. The integration of the abnormality-scaled features according to the above strategy resulted in a scalar called activation value, a:

$$a(t) = \sum_{i=1}^{n} f_i(t)^* v_i \tag{11}$$

where the f_i represent the abnormality-scaled feature values and the v_i denote the voting weights. For fault detection, the activation value was hard-limited with the threshold θ_v defined as the $max(a(t))$ within the sample set of κ normal features. A fault was assumed to have occurred in the gearbox if the activation value from any of the accelerometers was hard-limited. For fault detection, the voting weights for the general, gear, and bearing fault groups were determined as at 0.042, 0.067, and 0.056, respectively, with the voting threshold θ_v set between 0.1 and 0.17 for individual accelerometers.

The detection results for individual test sets obtained from SCBC are shown in Table 3. A desk in this table indicates normal conditions, whereas a 1 indicates the presence of a fault. The expected detection results are indicated inside parenthesis. For example, the results for Test 1 indicate that SCBC detected the presence of faults on Days 5, 6 and 8, whereas faults were expected to be present from Day 5 to Day 9. Of course, it should be noted that the gearbox was not inspected on a daily basis. As such, the actual condition of the gearbox is unknown for each day of the tests. In Test 1, which was run for 9 days, a fault was actually observed only on Day 9 (indicated by 1*) during routine inspection of the gearbox. However, based on an inspection of the vibration features, it was estimated that the fault could have been present as early as Day 5. For other tests, the days when the faults were actually observed are also indicated by 1*.

In order to evaluate the effectiveness of SCBC, its performance was compared with Kohonen's Feature Mapping (KFM) and Adaptive Resonance Theory (ART2). Although KFM is not suitable for on-line fault detection due to its demand for sample features from both the normal and fault categories, it is considered here so as to provide a basis for evaluating the performance of SCBC in classification. KFM was trained with 100 sweeps through the training batch with the learning rate set equal to the inverse of the number of the training sweeps [14], and its neighbourhood function was set to 0.5. The detection results from KFM are shown in Table 4. For ART2, the features a,b,c,d,e, and θ [15] were set to 10, 10, 0.01, 0.99, 0.001, and 0.2, respectively. The vigilance for ART2 was selected individually for each accelerometer between 0.76 and 0.96 for best detection

Table 3. Fault detection results from SCBC for the 5 tests. A dash indicates normality and a 1 represents the presence of a fault. For reference, the expected faults, determined by an expert, are included inside the parenthesis with a * to indicate the observed fault

	SCBC: Predicted and actual failures				
Day	Test 1	Test 2	Test 3	Test 4	Test 5
1	- (-)	- (-)	- (-)	- (-)	- (-)
2	- (-)	- (-)	- (-)	- (-)	- (-)
3	- (-)	- (-)	1 (1)	- (-)	- (-)
4	- (-)	1 (-)	1 (1*)	1 (-)	- (-)
5	1 (1)	1 (-)	- (-)	- (-)	- (-)
6	1 (1)	- (-)	- (-)	- (-)	- (-)
7	- (1)	- (-)	- (-)	- (-)	- (-)
8	1 (1)	- (-)	- (-)	- (-)	- (1)
9	- (1*)	- (-)	- (1*)	- (-)	1 (1)
10			- (-)	1 (1)	1 (1)
11			- (1)	1 (1)	- (1*)
12			1 (1)	1 (1*)	
13			- (1*)	1 (-)	
14				1 (1)	
15				1 (1*)	

Table 4. Fault detection results from Kohonen's Feature Mapping (KFM) for the 5 tests. A dash indicates normality and a 1 represents the presence of a fault. For reference, the expected faults, determined by an expert, are included inside the parenthesis with a * to indicate the observed fault

	KFM: Predicted and actual failures				
Day	Test 1	Test 2	Test 3	Test 4	Test 5
1	- (-)	- (-)	- (-)	- (-)	- (-)
2	- (-)	1 (-)	- (-)	- (-)	- (-)
3	- (-)	- (-)	1 (1)	- (-)	- (-)
4	- (-)	- (-)	1 (1*)	- (-)	- (-)
5	1 (1)	- (-)	1 (-)	- (-)	1 (-)
6	- (1)	1 (-)	1 (-)	- (-)	- (-)
7	1 (1)	1 (-)	1 (-)	1 (-)	1 (-)
8	- (1)	1 (-)	1 (-)	1 (-)	1 (1)
9	1 (1*)	1 (-)	1 (1*)	1 (-)	1 (1)
10			1 (-)	- (1)	- (1)
11			1 (1)	1 (1)	1 (1*)
12			1 (1)	1 (1*)	
13			1 (1*)	1 (-)	
14				- (1)	
15				1 (1*)	

Table 5. Fault detection results from ART2 for the 5 tests. A dash indicates normality and a 1 represents the presence of a fault. For reference, the expected faults, determined by an expert, are included inside the parenthesis with a * to indicate the observed fault

	ART2: Predicted and actual failures				
Day	Test 1	Test 2	Test 3	Test 4	Test 5
1	- (-)	- (-)	- (-)	- (-)	- (-)
2	- (-)	- (-)	1 (-)	- (-)	- (-)
3	- (-)	- (-)	- (1)	- (-)	- (-)
4	- (-)	- (-)	- (1*)	- (-)	- (-)
5	1 (1)	- (-)	- (-)	- (-)	- (-)
6	- (1)	- (-)	- (-)	- (-)	- (-)
7	1 (1)	- (-)	- (-)	- (-)	- (-)
8	1 (1)	- (-)	- (-)	- (-)	- (1)
9	- (1*)	- (-)	- (1*)	- (-)	- (1)
10			- (-)	- (1)	1 (1)
11			1 (1)	- (1)	1 (1*)
12			1 (1)	- (1*)	
13			1 (1*)	1 (-)	
14				1 (1)	
15				1 (1*)	

results. The detection results from ART2 are shown in Table 5.

For brevity the summary of detection results from SCBC, KFM, and ART2 is presented in Table 6. The performance of each of these classifiers is measured in terms of the number of correct classifications (both normal and fault), false alarms, and undetected faults. In Table 6, when the classifier produces the same output as the one inside the parentheses it is counted as correct classification. A false alarm represents a case where a fault is detected while the gearbox is normal, and an undetected fault denotes the case where the presence of a fault is not detected. The results in Table 6 indicate that for Test 1, SCBC performed correct classification 7 of the 9 days, and that the KFM produced similar detection results for this test. For Tests 2, 3, 4, and 5, SCBC showed superior performance as compared to KFM and ART2.

According to the results in the last column of this table, which shows the total number of correct classifications, false alarms, and undetected faults, SCBC produced correct classification on 46 days of the 57 days, produced 4 false alarms, and left 7 faults undetected. KFM was able to perform correct classification on 36 days, produced 16 false alarms, and left 5 faults undetected. Although false alarms do not result in safety hazards, like undetected faults, they are still considered serious flaws in a detection system because they often lead to unnecessary maintenance operations and reduced confidence in the detection system. ART2 was able to perform correct classification for 45 days, produced 2 false alarms, and left 10 faults undetected. Even though ART2 produced results comparable to SCBC in correct classifications and false alarms, it was not able to detect faults in Test 3 on either Days 3 or 4, and in Tests 4 in any of the Days 10, 11, and 12. Considering this, SCBC provided a better overall number of correct detection, undetected faults and false alarms as compared to KFM and ART2. That SCBC can provide comparable detection results as KFM and ART2 despite its less restrictive nature, is indeed reassuring.

Table 6. The summary of the detection results of SCBC, KFM and ART2 in terms of CC – Correct Classification, FA – False Alarms, and UF – Undetected Faults

		Summary of Detection					
		Test 1	Test 2	Test 3	Test 4	Test 5	Total
CC	SCBC	7	7	10	13	9	46
	KFM	7	4	8	9	8	36
	ART2	7	9	9	11	9	45
FA	SCBC	0	2	0	2	0	4
	KFM	0	5	5	4	2	16
	ART2	0	0	1	1	0	2
UF	SCBC	2	0	3	0	2	7
	KFM	2	0	0	2	1	5
	ART2	2	0	3	3	2	10

5. Conclusion

A new unsupervised pattern classifier is introduced for abnormality-scaling of vibration features. This unsupervised pattern classifier, referred to as the Single Category-Based Classifier (SCBC), scales features for abnormality by comparing them with the normal values of vibration features alone. As such, SCBC does not require any features associated with various faults. Two adaptation schemes, namely primary adaptation and secondary adaptation, are also introduced for updating the weights of SCBC to cope with noise and small variations in the operating conditions. The effectiveness of SCBC is demonstrated in fault detection of an OH-58A helicopter gearbox. In order to perform fault detection, a weighting network with predefined voting weights is utilized for integrating the abnormality-scaled features. The fault detection results from this network are compared with two predominant unsupervised methods: Kohonen's Feature Mapping (KFM) and Adapative Resonance Theory (ART2). The results from the OH-58A gearbox indicate that the overall performance of SCBC measured in terms of the number of correct classifications, false alarms and undetected faults is comparable to that of KFM and ART2. These results, coupled with the less restrictive nature of SCBC, indicate that SCBC is a superior classifier for abnormality-scaling of vibration features for fault diagnosis.

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